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A heuristic approach for the evaluation of Physical Protection System effectiveness

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ABSTRACT

Physical Protection System (PPS) is essential for each nuclear power plant to safeguard its nuclear materials and nuclear facilities from theft, robbery, illegal transport and sabotage. This paper presents a novel method (HAPPS) combined with Estimate of Adversary Sequence Interruption (EASI) method and heuristic approach (Ant Colony Optimization, ACO) for analyzing and evaluating the PPS effectiveness of NPPs. Import 2-D engineering drawings into the analysis application, identify the information contained in the model, and use the HAPPS method as search algorithm to seek the vulnerable adversary intrusion and escape path under certain conditions. The results of PPS effectiveness analysis will provide a detailed technical feedback for redesigning PPS.

1. Introduction

Each Nuclear Power Plant (NPP) is protected by a Physical Protection System (PPS) which integrates personnel, procedures and systems for the protection of nuclear material and facilities against theft, sabotage and other malicious human actions. The effectiveness of a PPS is characterized by its ability to withstand a possible attack and prevent adversaries from achieving their objectives. Since human adversaries can learn and adapt, a PPS has to be updated constantly to compensate for and defeat the new capabilities or tactics of adversaries. It is imperative to evaluate the effectiveness of PPS whenever the system design or the conditions of use change significantly (Vintr et al., 2012).

Nowadays, the design of PPS for a NPP is based on risk assessment and risk management principles where risk assessment identifies the potential threats that exist as well as their likelihood and consequences, while risk management is used for the scheme options, comparisons and tradeoffs. The evaluation of PPS effectiveness is an integral part of risk assessment and serves as a basis for assessing whether the design of a PPS is able to decrease the risk resulting from a possible attack to an acceptable level.

Several PPS effectiveness evaluation methods have been proposed so far, among which "Estimate of Adversary Sequence Interruption (EASI)" developed by the Sandia National Laboratory (SNL) in the 1970s is the milestone. The EASI method is based on 1-D models and provides a basis for evaluating the probability of ceasing the attack based on the detection, delay, response, and communication characteristics of PPS. The characteristic of EASI model in selecting one path with a threat specified in advance makes it easy-to-use on one hand, and is viewed as its main disadvantage on the other hand. Despite the other limitations of the EASI model in identifying the most vulnerable intrusion paths and considering alarm assessment, it is so far the general method to assess the PPS of a NPP (Garcia, 2007). In the 1980s, the SNL developed another method called "Systematic Analysis of Vulnerability to Intrusion (SAVI)" (Matter, 1988; Sandia National Laboratory, 1989). Similar to the EASI method, the SAVI method is also based on 1-D models. However, it uses an adversary sequence diagram to analyze all possible and the most vulnerable paths of an attack. The SAVI method utilizes changeable characteristics of PPS such as the level of design basis treat, adversary tactics, the operating condition of a building, and a detailed characteristic of protective elements. The SAVI method can also deal with the probability of alarm assessment and applies cumulative detection probability to a so-called critical detection point instead of the point estimations. One of the major limitations of the SAVI method is that it uses the shortest distance between protective layers which is a rather conservative consideration. In spite of all the limitations, the SAVI method has been widely used. In addition to the two methods stated above, a method named "Analytic System and Software for Evaluating

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Safeguards and Security (ASSESS)" (Al-Ayat et al., 1989, 1990) was presented by the U.S. Department of Energy (DOE). The ASSESS method considers the risks not only from outsiders but also from insiders and colluding insiders. It is based on SAVI but is much more complex.

The methods based on 1-D models may lead to an inappropriate set of the most vulnerable paths due to the lack of detailed description on the actual system layout in the 1-D models. To overcome this limitation, the researchers of Korea Institute of Nuclear Nonproliferation and Control released a novel method named "Systematic Analysis of Physical Protection Effectiveness, SAPE" (Jang et al., 2009) which is based on a 2-D map model of PPS with divisions making up a net. The area of the PPS is divided into grids to form a net. Since the complexity of calculations rises exponentially along with the rising net density, a heuristic algorithm A* is applied to find the most vulnerable path and then evaluate the effectiveness of the PPS quantitatively. However, the accuracy, correctness, and speed of calculations are determined by the density of the net. There is therefore a need for experiments to be conducted to find the optimal net density. In addition, a suitable cost function has a direct influence on the effectiveness of A* algorithm, but it is usually difficult to obtain.

In summary, the effectiveness of a PPS depends on the most vulnerable path that the adversary may penetrate. The most vulnerable path of a PPS is the global optimal path of intrusion from the adversary's point of view. This paper presents a methodology of vulnerable path analysis based on the Ant Colony Optimization (ACO) algorithm (Coloring et al., 1992) which is a bio-inspired approach based on the foraging behavior of ants and has been widely applied to optimization problems modeled by graphs, such as scheduling, planning and routing. A typical application of ACO algorithm is robot path planning of which the main task is to seek an optimal path for a robot moving from a known starting point to the designated terminal (Brand et al., 2010; Cong and Ponnambalam, 2009). One of the motivations of applying ACO algorithm is to enable a more effective path identification based on 2-D map models than A* algorithm by some distinguished characteristics of the ACO algorithm such as parallelism, self-organization and positive feedback. In addition, by ACO algorithm, both the global optimal paths of intrusion and escape can be obtained through one computer run which will make the evaluation of PPS effectiveness more efficient.

In this paper, a heuristic approach for the evaluation of Physical Protection System Effectiveness (HAPPS) is proposed. HAPPS method is combined EASI approach and ACO algorithm to analyze and evaluate the PPS of NPPs. Feasibility analysis of HAPPS method includes 1-D analysis and 2-D analysis has been given and a case study on the vulnerable adversary intrusion and escape path is presented.

2. Overview of Ant Colony Optimization algorithm

The ACO algorithm was initially proposed to search for an optimal path in a graph based on the behavior of ants seeking a path between their nest and a source of food (Coloring et al., 1992). The principle of ACO algorithm can be explained by "asymmetric double bridge experiment" (Deneubourg et al., 1991), as shown in Fig. 1. Given a graph with two paths, m ants (represented by red solid circles) try to find the minimum path that connects the source node (that represents the nest) with the destination node representing the food source. Ants move through the graph incorporating solution components to their local solution. For the ant k moving from node i to node j, the probability of incorporating the solution component j to the local solution built by the ant is:

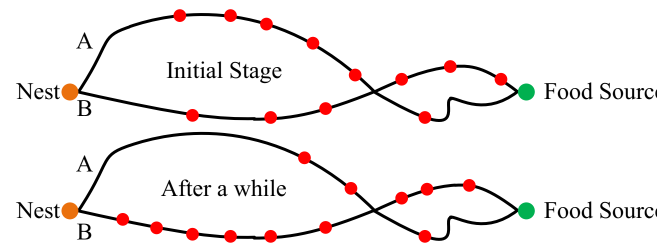

Fig. 1. Asymmetric bridge experiment of ACO algorithm.

$$P_{ij}^k(t) = \begin{cases} \frac{\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)}{\sum_{h\in N_i^k}^{n}\tau_{ih}^{\alpha}(t)\eta_{ih}^{\beta}(t)} & if\ j \in N_i^k \\ 0 & otherwise \end{cases} \tag{1}$$

Here τ_{ij} represents the heuristic function of the problem and describes the goodness of incorporating the solution component j. η_{ij} contains the pheromone value and represents the quality of past solutions that have included the solution component j. α and β are parameters of the algorithm that measure the influence of the pheromones and the heuristic. And N_i^k contains the feasible nodes available from node i according to the local solution built by the ant k.

Communication among ants is performed using the environment. Once any ant has built a complete solution, the ant goes back to the nest and it deposits in the path some pheromones that will guide other ants in their process of building their own solution. The quantity of pheromone deposited between two nodes i and j, represented by η_{ij}, is proportional to the quality of the solution built by the ants. This means that better solutions will be represented in pheromones with higher pheromone value and thus, this paths will attract other ants according to formula (1). In order to avoid non-optimal solutions attracting a majority of ants, pheromones are forced to decrease according to an evaporation rate ρ.

In the initial stage, the same pheromone equal to a constant, $\tau_{ij}(0) = C$. If $\tau_{ij}(0)$ is too small, local optimum would be easy to occur; otherwise, if too large, the pheromone would play a small role in the guidance of ant search directions. The value of $\tau_{ij}(0)$ assigns good or bad influence on ACO performance. The initial C can be defined as

$$C = m/C^{nn} \tag{2}$$

The pheromone that all ants left should be as historical data to deposit, then, the pheromone in any area can be updated by the iterative formula:

$$\tau_{ij}(t+n) = \rho \cdot \tau_{ij} + \sum_{k=1}^{m} \Delta\tau_{ij}^k(t, t+n) \tag{3}$$

where, $0 < \rho \leqslant 1$ is the evaporation rate that controls the pheromone concentration on each path; $\Delta\tau_{ij}^k$ is the pheromone deposited by the ant k moving from i to j area. In this paper, $\Delta\tau_{ij}^k$ can be calculated by the ant-cycle system (Dorigo et al., 1991)

$$\Delta\tau_{ij}^k = \begin{cases} Q/TL_k & if\ the\ k^{th}\ ant\ traverses(i,j) \\ 0 & others \end{cases} \tag{4}$$

here, TL_k is the length of the tour of the ant k found in the current iteration; Q is an adjustable constant and means the total pheromone released by the ant on the path at one cycle.